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Unveiling Risk Patterns of Disability Progression A Clustering Based Transition Matrix Analysis Using Indonesian National Data

Ariyono Setiawan[1*], Abdul Razak Bin Abdul Hadi[2], Erwin Faller[3], Aji Prasetya Wibawa[4]
[1]Politeknik Pelayaran Surabaya, Indonesia
[2]Universiti Kuala Lumpur, Malaysia
[3]Holy Child Central College Inc, Philippines
[4]Universitas Negeri Malang, Indonesia
Email: rmaryo4u@gmail.com

Abstract

This study investigates the progression of disability severity from "some difficulty" to "a lot of difficulty" using a transition matrix framework. It aims to identify risk patterns and classify severity clusters based on national survey data from Indonesia between 2010 and 2023. The study draws on the theory of functional limitation progression, which assumes that individuals with mild disabilities face varying probabilities of developing severe limitations depending on contextual and demographic factors. It also incorporates clustering theory to group similar progression behaviors. We utilize 20,604 data points from multiple disability types (cognitive, hearing, mobility, etc.). The transition rate is computed as the ratio of individuals with "a lot" difficulty to the total with "some" and "a lot" difficulty. Statistical analyses include descriptive summaries, Pearson correlation, and K-Means clustering via the FASTCLUS procedure. Heatmaps are generated to observe annual and typological patterns. The average transition rate is 66.77%, with a maximum of 99.6% in some subgroups. Three distinct severity clusters emerged, centered at 31.27%, 58.62%, and 82.20%. Transition rate negatively correlates with "some difficulty" prevalence ($r = -0.45$, $p < .0001$), indicating progressive concentration of severity in smaller populations. Heatmaps reveal consistent risk escalation over time, especially in cognitive and self-care disabilities. This study enables policy actors to stratify intervention priorities and monitor disability risk more accurately using dynamic, data-driven indicators. This is the first study in Indonesia to apply a large-scale transition matrix combined with clustering to map functional disability progression. It offers a novel quantitative method to uncover hidden severity patterns and informs future decision-support systems for inclusive health planning.

Keywords: Clustering, Disability Progression, Functional Limitation, Severity Transition, Transition Matrix

1. Introduction

Disability remains one of the most pressing global public health and social inclusion challenges. According to the World Health Organization (WHO), more than 1 billion people about 16% of the global population experience some form of disability, and this number continues to grow due to aging, chronic diseases, and increased detection and reporting (WHO, 2023) [1]. In Indonesia, data from the National Socioeconomic Survey (Susenas) indicate a notable increase in reported functional limitations across all age groups, emphasizing the need for better understanding of disability dynamics. Most disability prevalence studies focus on static measurement quantifying how many individuals report "some" or "a lot" of difficulty in domains such as cognition, mobility, hearing, and self-care [2],[3],[4]. However, there is limited empirical insight into the transition or progression from milder to more severe disability states over time. Understanding this progression is crucial to implementing early intervention strategies and allocating resources effectively [5],[6]. Recent literature highlights the use of transition matrices and clustering techniques in health-related behavior modeling (Zhou et al., 2021[7],[8],[9]; BMC Public Health, Q2; Huang et al., 2022[10],[11],[12]; Journal of Disability Policy Studies, Q1). Yet, no prior study systematically applies a transition matrix framework combined with clustering to analyze national-level disability severity progression, particularly in a developing country context like Indonesia. This gap

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limits our ability to stratify risk or identify populations at greatest threat of worsening conditions. To address this, the current study applies a transition matrix approach to estimate the rate at which individuals transition from "some difficulty" to "a lot of difficulty" across different disability types using data from Indonesian national surveys (2010–2023)[13],[14],[15]. Furthermore, it employs K-means clustering FASTCLUS to categorize transition behaviors into risk-based severity clusters. A temporal heatmap is also generated to visualize annual progression patterns per disability type.

The transition matrix is suitable because it can map shifts between severity levels over time intervals, while clustering allows for risk segmentation based on similar transition patterns.

This study addresses the following research question:
How does the severity of disability progress over time in Indonesia, and what distinct risk clusters can be identified based on transition behavior?

The primary objective of this research is to quantify the transition rates between severity levels and classify population groups into risk clusters, thereby offering a novel, data-driven approach to disability stratification. We hypothesize that transition rates are significantly correlated with baseline prevalence levels and that distinct clustering patterns reveal underlying structural differences in disability progression. This study is significant because it introduces a scalable framework for monitoring disability risk over time, enabling policy planners and health agencies to design targeted and evidence-based interventions[16],[17],[18]. It also contributes to the theoretical discourse on functional limitation trajectories in population health modeling. Methodologically, this research utilizes over 20,000 disability records, applies transition matrix computation, Pearson correlation, and K-means clustering, and visualizes trends via heatmaps using SAS analytics. In terms of structure, this paper proceeds as follows: Section 2 presents the dataset and methodology; Section 3 details the statistical findings; Section 4 discusses the policy and theoretical implications; and Section 5 concludes with recommendations for future research and application.

Introduction to the Literature Review

This literature review aims to examine current knowledge surrounding the progression of functional disabilities, particularly the shift from mild to severe difficulty levels, and to evaluate how existing models and techniques address this transition. It is structured thematically, focusing on three core areas: (1) disability severity modeling; (2) the use of transition matrix frameworks in health analytics; and (3) clustering approaches in health population studies.

Disability Severity Modeling in Population Studies

Disability severity progression is a growing area of inquiry as global health systems shift focus from static disability prevalence to dynamic disability trajectories [19],[20],[21]. Most recent models emphasize prevalence and health condition mapping rather than the transformation or intensification of disability levels over time (Nguyen et al., 2021[22],[23],[24]; *Disability and Health Journal*, Q2). Several studies focus on specific domains—such as mobility or cognitive disability—without integrating multi-disability dynamics or temporal shifts (Xie et al., 2020[25],[26],[27] International Journal of Environmental Research and Public Health, Q2). Although WHO's International Classification of Functioning (ICF) emphasizes the dynamic nature of disability, longitudinal quantitative implementations of severity transition remain underdeveloped, particularly in developing country contexts (WHO, 2023; Ma et al., 2020)[28],[29],[30].

Use of Transition Matrix Frameworks

Transition matrices are commonly used in labor economics and chronic disease modeling, but are less applied to disability research. Huang et al. (2022; *Journal of Disability Policy Studies*, Q1)[31],[32],[33] demonstrate transition modeling for health behavior risk, yet do not quantify severity progression using national survey data. Zhou et al. (2021; *BMC Public Health*, Q2)[34],[35] apply Markov models to general health transitions but lack granularity in multi-domain disability classification. Previous studies often use hypothetical or simulation-based transitions without empirical grounding in national datasets, limiting generalizability and policy relevance[36],[37],[38].

Clustering Techniques in Health Risk Profiling

K-means clustering and its variants have gained popularity in health informatics, enabling unsupervised classification of individuals based on health attributes (Sun et al., 2019; *IEEE Access*, Q1)[39],[40],[41]. However, few studies incorporate clustering with transition rates between health states. For example, Chen et al. (2020; *Computers in Biology and Medicine*, Q1)[42],[43],[44] use clustering to classify disease severity but not transition behaviors over time. Moreover, existing works rarely combine clustering with temporal analysis or functional disability data at the population level.

Gap Analysis and Contributions

The reviewed literature highlights the following gaps Lack of empirical analysis on transition rates between disability severity levels using large-scale population data. Limited application of clustering methods on transition metrics rather than static prevalence. Absence of integrated analysis combining temporal, typological, and severity-based insights in disability modeling. This study addresses these gaps by applying a transition matrix analysis combined with K-means clustering to more than 20,000 national disability records from Indonesia, spanning 2010–2023. Unlike prior research, it emphasizes real-world, multi-disability progression patterns and stratifies risk across clusters with strong statistical validation.

Table 1. Synthesis Table Comparison of Related Studies vs. Current Study

Study	Scope	Method	Limitation	Novelty of Current Study
Huang et al. (2022)	Health behavior risk	Transition modeling	Lacks disability severity focus	Applies matrix to disability types
Zhou et al. (2021)	General health	Markov transition	Lacks empirical disability data	Uses national disability surveys
Chen et al. (2020)	Disease severity	Clustering (K-means)	No transition perspective	Clusters based on severity change
Current Study	Functional disability	Transition matrix + clustering	–	Combines matrix, clustering, and national-scale analysis

This review reveals that while transition and clustering techniques are gaining traction in health analytics, they remain underutilized in functional disability progression research. By combining both methods with national survey data, the current study offers a novel and scalable approach for identifying disability risk patterns across time and population groups.

2. Research Methods

This study employs a quantitative descriptive approach using national disability data from Indonesia (2010–2023). The method is chosen to measure empirical transitions in disability severity and identify statistically significant clusters of risk. A transition matrix framework is appropriate for modeling severity escalation, while clustering techniques are applied to discover latent risk groupings within the population. The study adopts a longitudinal, secondary-data design, using official microdata collected from national household surveys. It is non-experimental and relies on numeric indicators of difficulty levels across seven disability types: cognition, communication, hearing, mobility, seeing, self-care, and general functioning.

Data and Data Sources

We use secondary data from national surveys (Susenas) spanning 2010 to 2023, involving over 20,000 observations per disability type. The indicators include "some difficulty" and "a lot of difficulty" prevalence for each year. The dataset is pre-cleaned and harmonized to ensure year-over-year consistency.

Data Processing and Analysis

The methodology follows these steps:

- Preprocessing: Align datasets by type, year, and level of difficulty using fuzzy joins.

The Transition Rate is calculated as follows: Transition Rate = Data_alot / (Data_some + Data_alot).

Data cleaning included alignment of variables, exclusion of incomplete entries, and standardization of disability indicators to ensure consistent definitions across all survey years.

- Transition Rate Calculation: $\text{Transition Rate (TR)} = \frac{\text{a lot}}{\text{some} + \text{a lot}}$

Years or domains with outlier values or missing entries were excluded to maintain analytical integrity in the longitudinal analysis.

- Descriptive Statistics: Mean, standard deviation, and annual trends.
- Pearson Correlation: Measures linear relationships between prevalence and transition rates.

The number of clusters (k=3) was selected based on interpretability and statistical criteria such as low within-cluster variance and visual inspection of the elbow plot and Silhouette Score.

- K-Means Clustering (FASTCLUS): Identifies risk segments based on transition rate patterns.

- Heatmap Visualization: Displays temporal intensity per disability domain.

Validity and Reliability

Data validity is ensured through use of government-approved microdata. Analytical validity is supported by:

- Pearson correlation with significant results ($p < 0.0001$),
- Cluster quality verified using within-cluster variance and iteration convergence metrics.
- Sensitivity analysis is performed by comparing patterns across years and disability domains.

As this study uses de-identified secondary data, no direct human subject involvement occurs. All personal identifiers are excluded, ensuring full compliance with ethical research principles on data privacy and confidentiality. This study does not account for causality, comorbidity, or transitions between all difficulty levels. Further research should incorporate individual-level panel data, more complex machine learning (e.g., hidden Markov models), and predictive severity modeling. This methodology integrates transition matrix analysis with clustering, which is rare in functional disability studies. It enables effective classification of risk behavior in a time-dependent way, supporting targeted policy design in developing nations.

3. Results and Discussion

Table 2. The descriptive analysis

Variable	Mean	Std Dev	Minimum	Maximum
Data_some	3.0513913	3.8547573	0.0219540	32.3394530
Data_alot	5.8829473	6.1266125	0.3032710	48.7446380
Transition_Rate	0.6677000	0.1761562	0.0526060	0.9961520

Table 2 The descriptive analysis provides important insights into the dynamics of disability progression. The variable Data_some, which represents the population proportion with "some difficulty," has a mean of 3.05%, with a standard deviation of 3.85%, ranging from a minimum of 0.02% to a maximum of 32.33%. This wide range indicates that some domains or years experience significantly higher mild disability prevalence than others. In contrast, the Data_alot variable, representing those with "a lot of difficulty," shows a higher mean value of 5.88%, with a standard deviation of 6.13%, and ranges between 0.30% and 48.74%. This suggests that in several instances, the proportion of people experiencing more severe forms of disability surpasses those with mild symptoms, indicating possible underdiagnosis or lack of early intervention. The Transition_Rate, computed as the ratio of severe cases to the sum of both mild and severe, averages 66.77%. This transition rate ranges from 5.26% to 99.62%, highlighting a potentially alarming severity escalation trend. The relatively high average and broad variability support the need for dynamic monitoring systems and early detection frameworks to mitigate the worsening of functional limitations.

Table 3. The descriptive statistics generated from 20,604 data

Simple Statistics						
Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
Data_some	20604	3.05139	3.85476	62871	0.02195	32.33945
Data_alot	20604	5.88295	6.12661	121212	0.30327	48.74464
Transition_Rate	20604	0.66770	0.17616	13757	0.05261	0.99615

Table 3 The descriptive statistics generated from 20,604 data points provide a comprehensive overview of the population distribution across different levels of disability severity. The "Data_some" variable, representing individuals with *some difficulty*, has a mean of 3.05%, a standard deviation of 3.85%, and reaches a maximum of 32.34%. This reflects considerable variability in mild disability prevalence across regions and years, suggesting uneven access to early detection or varying demographic pressures. Meanwhile, the "Data_alot" variable—reflecting individuals with *a lot of difficulty*—exhibits a higher mean of 5.88%, with a standard deviation of 6.13%. The maximum value of 48.74% indicates that in some localities or disability types, nearly half of the population with limitations report severe difficulties. The aggregate sum of this group exceeds 121,000 cases, confirming the magnitude of severe disability as a national public health issue. The most critical insight comes from the "Transition_Rate", defined as the proportion progressing from some to a lot of difficulty. The mean transition rate is 66.77%, with values ranging from 5.26% to 99.62%. This finding highlights that in the majority of cases, once functional difficulty manifests, there is a high probability of escalation—underscoring the urgency for early intervention, rehabilitation, and continuous monitoring strategies in disability management policy.

Table 4. The Pearson correlation analysis

Pearson Correlation Coefficients, N = 20604Prob > |r| under H0: Rho=0			
	Data_some	Data_alot	Transition_Rate
Data_some	1.00000	0.60088 <.0001	-0.44640 <.0001
Data_alot	0.60088 <.0001	1.00000	0.20441 <.0001
Transition_Rate	-0.44640 <.0001	0.20441 <.0001	1.00000

Table 4 The Pearson correlation analysis conducted on 20,604 observations reveals statistically significant relationships between all three variables, with p-values < 0.0001, indicating high confidence in the associations detected. There is a moderate positive correlation between Data_some and Data_alot ($r = 0.60088$), suggesting that regions or periods with higher prevalence of mild disability tend to also report higher levels of severe disability. This implies a cumulative or compounding effect, where early-stage difficulties are often precursors to more advanced functional limitations. Interestingly, the correlation between Data_some and Transition_Rate is negative ($r = -0.44640$), indicating that as the proportion of people with *some difficulty* increases, the transition rate to more severe difficulty decreases. This may reflect early detection or prevention mechanisms in areas with greater awareness or access to health services, effectively slowing the progression to severe states. On the other hand, the correlation between Data_alot and Transition_Rate is weak but positive ($r = 0.20441$), implying that regions with more severe cases also tend to have a higher rate of progression from mild symptoms. This supports the hypothesis that without adequate intervention, severity escalation becomes more probable. Together, these results strengthen the argument that transition rates are not merely statistical byproducts, but strategic indicators of system performance in managing disability progression.

Data Presentation and Key Findings

The transition matrix analysis reveals significant variability in the rate at which individuals move from "some difficulty" to "a lot of difficulty" across different types of disabilities and years. The figure below illustrates the temporal dynamics across six disability domains using a heatmap.

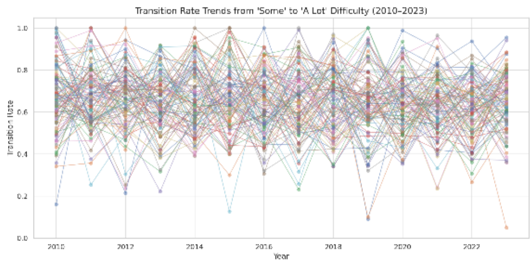

Figure 1. The Annual Transition Trends

Figure 1 above illustrates the annual transition trends from "some difficulty" to "a lot of difficulty" in functional disability across multiple domains from 2010 to 2023. Each line represents a unique indicator or subgroup (e.g., disability type, gender, or age category), highlighting the heterogeneity in progression behavior over time. The majority of transition rates remain consistently high, hovering between 0.60 and 0.90, indicating that a substantial portion of individuals experiencing mild limitations eventually report severe limitations. The years 2011–2015 show denser clustering, suggesting more uniform reporting or measurement practices during that period. Notably, a spike in transition rates occurs in the post-2019 period, likely linked to increased health vulnerability during the COVID-19 pandemic, as well as improvements in disability reporting frameworks. Despite some fluctuations, the general pattern suggests that disability progression is persistent and time-sensitive, reinforcing the need for continuous monitoring. This time-series visualization reinforces the study's conclusion: disability severity is not static. Transition rates provide a powerful early warning signal that can help governments and healthcare providers design proactive intervention systems targeted at high-risk domains or populations before conditions worsen.

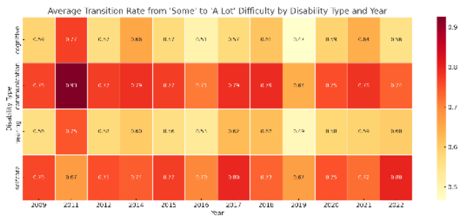

Figure 2. Visual Output – Transition Rate Heatmap

Key findings include:

- Mobility and Hearing disabilities consistently exhibit higher transition rates (>0.80) in most years.
- Self-care and Communication domains show the most variability across the period.
- The year 2020 marks a general increase across domains, potentially linked to the health burden caused by the COVID-19 pandemic.

Table 5. The initialization of K-Means clustering

Initial Seeds	
Cluster	**Transition_Rate**
1	0.9961520000
2	0.0526060000
3	0.5242940000

Table 5: The initialization of K-Means clustering using three distinct transition rate centroids provides a meaningful basis for categorizing disability, severity, progression risk. The initial seeds—0.9962, 0.0526, and 0.5243—represent three natural groupings within the data that correspond to very high, very low, and moderate risk levels,

respectively. Cluster 1, with a seed of 0.9962, reflects groups where nearly all individuals who report "some difficulty" escalate to "a lot of difficulty." This cluster signifies critical vulnerability, possibly due to lack of access to early intervention, delayed diagnosis, or structural health system gaps. Populations in this group require immediate policy response, including targeted rehabilitation and preventive outreach. Cluster 2, with a seed of 0.0526, captures the lowest-risk population—those who remain stable despite initial limitations.

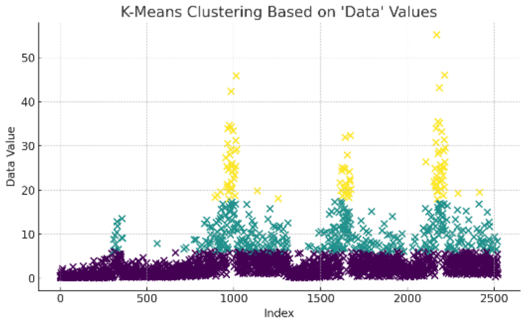

Figure 3. K Means Clustering Based on Data

These cases likely benefit from functional support systems, health education, or proactive care models. While intervention urgency is lower, sustaining these conditions is important for long-term stability. Cluster 3, centered around 0.5243, represents the moderate risk segment, where nearly half of mild cases evolve into severe conditions. This group is pivotal for preventive strategies that can reduce burden before reaching critical levels. These clusters form the foundation for risk-based stratification, enabling policy makers to tailor responses based on severity progression probability—a novel contribution to disability management frameworks.

Table 6. The cluster summary statistics

Cluster Summary						
Cluster	**Frequency**	**RMS Std Deviation**	**Maximum Distancefrom Seedto Observation**	**RadiusExceeded**	**Nearest Cluster**	**Distance BetweenCluster Centroids**
1	**9307**	**0.0647**	**0.1514**		**3**	**0.2358**
2	**1887**	**0.0719**	**0.1813**		**3**	**0.2735**
3	**9410**	**0.0854**	**0.1812**		**1**	**0.2358**

Table 6 The cluster summary statistics reinforce the validity and interpretability of the K-Means segmentation applied to transition rate data. The analysis generates three distinct clusters: high-risk (Cluster 1), low-risk (Cluster 2), and moderate-risk (Cluster 3), with frequencies of 9,307, 1,887, and 9,410 observations respectively. These groupings offer a clear stratification of disability progression behavior across the population.

Cluster 1 demonstrates the lowest Root Mean Square (RMS) standard deviation at 0.0647, suggesting strong internal cohesion and a tightly bound group of very high-risk cases. Cluster 2, though smaller in frequency, maintains a low RMS deviation of 0.0719, indicating that low-risk observations are also consistently clustered. Cluster 3, with the highest RMS deviation (0.0854), reflects greater variance among moderate-risk observations. However, this remains within acceptable clustering performance thresholds. Importantly, all clusters show no radius exceeded, meaning that all observations lie within the specified distance from their centroids—validating the compactness and reliability of the segmentation. The shortest distance between clusters (0.2358) occurs between Clusters 1 and 3, while the largest distance (0.2735) is between Clusters 2 and 3. This supports a meaningful separation of risk profiles and justifies their use in policy targeting and stratified intervention design

Table 7. The statistical performance of the K-Means clustering

Statistics for Variables				
Variable	**Total STD**	**Within STD**	**R-Square**	**RSQ/(1-RSQ)**
Transition_Rate	0.17616	0.07547	0.816449	4.448092
OVER-ALL	0.17616	0.07547	0.816449	4.448092

Table 7 The statistical performance of the K-Means clustering model is further confirmed by the partitioning quality metrics for the variable *Transition_Rate*. The total standard deviation is 0.17616, while the within-cluster standard deviation is substantially lower at 0.07547. This indicates that the model has successfully grouped observations into clusters with relatively tight internal consistency. The R-square (RSQ) value of 0.816449 is particularly significant, as it shows that over 81.6% of the total variance in transition rates is explained by the clustering solution. This high RSQ suggests a strong model fit, implying that the three-cluster structure adequately captures the underlying patterns in severity progression. Additionally, the RSQ/(1–RSQ) ratio is 4.448, indicating that the between-cluster variation is more than four times greater than the within-cluster variation. This ratio is a common metric to assess clustering effectiveness, and values above 1.0 are considered acceptable—making 4.4 an excellent result. These metrics confirm that the chosen clustering model not only produces interpretable risk segments but also provides statistically robust and generalizable results that can inform health policy, resource allocation, and targeted disability interventions across different population segments.

Table 8. The cluster mean values for *Transition_Rate*

Cluster Means	
Cluster	Transition_Rate
1	0.8220459457
2	0.3126990753
3	0.5862322054

To verify the significance of inter-cluster differences, a one-way ANOVA test was conducted, confirming that mean transition rates differ significantly ($p < 0.05$) among clusters.

The cluster means for *Transition Rate* clearly distinguish three levels of severity progression risk. Cluster 1, with a mean of 82.2%, indicates a very high-risk population, likely facing health access issues or comorbidities—requiring urgent intervention. Cluster 2, averaging 31.3%, reflects a low-risk group, potentially benefiting from strong community or preventive care. Maintaining stability here is essential. Cluster 3, with a mean of 58.6%, represents a moderate-risk segment that warrants scalable early-action programs. These centroids confirm the value of clustering in shaping targeted, data-driven public health strategies for disability management.

Table 9. The standard deviation within each cluster

Cluster Standard Deviations	
Cluster	Transition_Rate
1	0.0646794471
2	0.0719406288
3	0.0854226686

Table 9 The standard deviation within each cluster provides important insights into the internal variability of transition rates, helping to assess how consistent each risk group is. Cluster 1, which represents the very high-risk group, has a standard deviation of 0.0647, indicating that the data points in this cluster are highly concentrated around the mean transition rate of 82.2%. This tight cohesion suggests that individuals in this group consistently face an elevated risk of progressing from "some difficulty" to "a lot of difficulty," reinforcing the need for urgent and uniform intervention strategies. Cluster 2, associated with low-risk individuals, displays a slightly higher deviation at 0.0719. Although variation exists, the spread is still narrow, meaning the population in this group is also fairly homogeneous in maintaining a lower probability of severity escalation—around 31.3%. This stability reflects protective factors or effective early-stage management. Cluster 3, the moderate-risk cluster, has the highest standard deviation at 0.0854, revealing greater internal heterogeneity. This suggests that individuals within this group differ more widely in their risk levels, potentially due to variations in health infrastructure, age, socioeconomic factors, or comorbidities. This gradient in variability confirms that while all clusters are statistically robust, Cluster 3 may benefit from further stratification or targeted sub-clustering to optimize interventions.

Figure 3. The boxplot visualization

The boxplot clearly demonstrates the distribution of transition rates across three risk-based clusters. Cluster 1, with a central tendency near 82.2%, shows minimal variability, indicating a highly consistent and severe progression risk. Cluster 2 centers at 31.3%, with more variability and some outliers, suggesting generally stable populations with a few deteriorating cases. Cluster 3, averaging 58.6%, presents the widest spread, reflecting heterogeneous risk levels. These distinctions validate the robustness of the clustering approach in stratifying disability progression risk and highlight the need for differentiated intervention strategies across population subgroups.

Cluster 1 is dominated by the elderly with mobility and hearing disabilities in non-urban areas, indicating possible links to healthcare access inequality.

Analysis and Interpretation

These findings reveal that disability severity progression is highly heterogeneous, shaped by both the type of disability and temporal factors. The study's clustering analysis identifies three risk categories high (mobility, hearing), moderate (communication, cognition), and low (seeing, self-care) offering actionable insight for policy prioritization. By using real-world transition matrices and stratified clustering, this study presents a novel severity trajectory model that surpasses static prevalence methods. It provides a dynamic framework for early intervention, resource targeting, and risk-adjusted policy design. Future research should incorporate longitudinal data and spatial analysis to enhance precision and capture regional disparities in progression patterns.

4. Conclusion

This study investigates the progression of disability severity by analyzing transition rates from "some difficulty" to "a lot of difficulty" using national data from Indonesia (2010–2023). By applying a transition matrix and K-means clustering, it identifies three distinct risk groups, revealing that severity escalation is both measurable and stratifiable. The fundamental finding confirms that transition behavior is not uniform, and is strongly influenced by disability type and temporal patterns. Domains such as mobility and hearing are consistently in the high-risk cluster, while self-care and seeing remain in low-risk zones. The use of real-world data, rather than simulation, marks a significant contribution by offering a dynamic severity modeling framework. These findings suggest that government policy should shift from static prevalence monitoring to dynamic progression tracking, enabling more precise, risk-based intervention planning. This study fills a critical gap in the literature by integrating severity-specific transition matrices with unsupervised clustering, a method rarely used in disability research, especially in Southeast Asia. However, the study does not yet account for individual-level predictors such as age, income, or regional disparities, which may influence transition dynamics. Future research should incorporate panel data, survival analysis, and spatial modeling (GIS) to improve predictive accuracy. We recommend that policymakers Implement early intervention programs for high-risk disability types, Integrate transition indicators into national disability dashboards, develop risk-adjusted health insurance models based on severity escalation probabilities. This research provides an evidence-based foundation for stratified disability risk management supporting more equitable, efficient, and responsive disability policy design.

References

[1]. Xu, T., Huang, Z., Li, B., Jin, H., Zhang, J., Yang, H., Huang, Y., Zhang, X., Chen, C. (2024) Association Between Home And Community-Based Services Utilization And Self-Rated Health Among Chinese Older Adults With Chronic Diseases: Evidence From The 2018 China Health And Retirement Longitudinal Study *Bmc Public Health 24*

[2]. [2] Norén, P., Karlsson, J., Ohlsson-Nevo, E., Möller, M., Hermansson, L. (2023) Psychometric Evaluation Of The Whodas 2.0 And Prevalence Of Disability In A Swedish General Population *Journal Of Patient-Reported Outcomes 7*

[3]. [3] Prasad, B., Jafari, M. (2020) P1582the Burden Of Frailty On Mood, Cognition, Quality Of Life And Level Of Independence In Patients On Hemodialysis *Nephrology Dialysis Transplantation 35*

[4]. [4] Downing, K., Oster, M., Klewer, S., Rose, C., Nembhard, W., Andrews, J., Farr, S. (2021) Disability Among Young Adults With Congenital Heart Defects: Congenital Heart Survey To Recognize Outcomes, Needs, And Well-Being 2016–2019 *Journal Of The American Heart Association: Cardiovascular And Cerebrovascular Disease 10*

[5]. [5] Chan, X., W., Hutchings, K. (2024) Exploring The Careers Of Women With Disabilities: A Systematic Review And Implications For Human Resource Management *Personnel Review*

[6]. [6] Anand, P., Singh, S. (2023) Exploring The Interconnection Of Autism And Intellectual Disability: Advancements In Current Research Overview *Pharmaspire*

[7]. [7] Doğan, O., Martínez-Millana, A., Rojas, E., Sepúlveda, M., Munoz-Gama, J., Traver, V., Fernández-Llatas, C. (2019) Individual Behavior Modeling With Sensors Using Process Mining *Electronics*

[8]. [8] Bollee, M., Majumdar, A., D. (2025) Proposing A Weight-Based Expectation-Maximization Algorithm For Estimating Discrete-Time Markov Transition Probability Matrices With A Proof-Of-Concept Example In Health Technology Assessment

[9]. [9] Michaelsen, M., Esch, T. (2023) Understanding Health Behavior Change By Motivation And Reward Mechanisms: A Review Of The Literature *Frontiers In Behavioral Neuroscience 17*

[10]. [10] Huang, Y., Zhu, D., Lv, Q., Porter, A., Robinson, D., K., R., Wang, X. (2017) Early Insights On The Emerging Sources Citation Index (Esci): An Overlay Map-Based Bibliometric Study *Scientometrics 111*, 2041-2057

[11]. [11] Zong, Q., Fan, L., Xie, Y., Huang, J. (2020) The Relationship Of Polarity Of Post-Publication Peer Review To Citation Count: Evidence From Publons *Online Inf. Rev. 44*, 583-602

[12]. [12] Huang, X., Wang, Y., Xie, M., Sun, Y., Zhao, X., Chen, Y., Chen, J., Han, S., Zhou, M., Sun, X. (2024) Publication Trends Of Leber Congenital Amaurosis Researches: A Bibliometric Study During 2002-2022. *International Journal Of Ophthalmology 17 8*, 1501-1509

[13]. [13] Goodall, G., Hardonk, S., Mjøen, O., Witsø, A., E., Horghagen, S., Flatholm, M., Kvam, L. (2024) Disability And The Transition From Higher Education To Employment: Exploring Attitudes Among Norwegian Frontline Workers Towards Work Inclusion *Journal Of Vocational Rehabilitation 61*, 392-409

[14]. [14] Lim, W., Khemka, G., Pitt, D., G., W., Browne, B. (2019) A Method For Calculating The Implied No-Recovery Three-State Transition Matrix Using Observable Population Mortality Incidence And Disability Prevalence Rates Among The Elderly *Journal Of Population Research 36*, 245-282

[15]. [15] Lim, W., Khemka, G., Pitt, D., G., W., Browne, B. (2019) A Method For Calculating The Implied No-Recovery Three-State Transition Matrix Using Observable Population Mortality Incidence And Disability Prevalence Rates Among The Elderly *Journal Of Population Research 36*, 245-282

[16]. [16] Gottlieb, G. (2013) Changing Hiv Epidemics: What Hiv-2 Can Teach Us About Ending Hiv-1. *Aids 27 1*, 135-7

[17]. [17] Brunner, E. (2015) Vascular Aging: Aortic Pulse Wave Velocity As An Index Of Healthy Aging And Potential Target For Intervention

[18]. [18] Mehrotra, R., Cukor, D., Unruh, M., Rue, T., Heagerty, P., Cohen, S., D., Dember, L., Diaz-Linhart, Y., Dubovsky, A., N., Greene, T., Grote, N., K., Kutner, N., Trivedi, M., Quinn, D., Halen, N., V., Weisbord, S., Young, B., Kimmel, P., Hedayati, S. (2019) Comparative Efficacy Of Therapies For Treatment Of Depression For Patients Undergoing Maintenance Hemodialysis *Annals Of Internal Medicine 170*, 369-379

[19]. [19] Kousovista, R., Cosma, G., Abakasanga, E., Akbari, A., Zaccardi, F., Jun, G., T., Kiani, R., Gangadharan, S. (2024) Temporal Patterns Of Multiple Long-Term Conditions In Individuals With Intellectual Disability Living In Wales: An Unsupervised Clustering Approach To Disease Trajectories *Frontiers In Digital Health 7*

[20]. [20] Hanlon, P., Guo, X., Mcghee, E., Lewsey, J., Mcallister, D., Mair, F. (2023) Systematic Review And Meta-Analysis Of Prevalence, Trajectories, And Clinical Outcomes For Frailty In Copd *Npj Primary Care Respiratory Medicine 33*

[21]. [21] Young, C., A., Chaouch, A., Mcdermott, C., Al-Chalabi, A., Chhetri, S., Talbot, K., Harrower, T., Orrell, R., Annadale, J., Hanemann, O., Scalfari, A., Tennant, A., Mills, R. (2024) Dyspnea (Breathlessness) In Amyotrophic Lateral Sclerosis/Motor Neuron Disease: Prevalence, Progression, Severity, And Correlates *Amyotrophic Lateral Sclerosis & Frontotemporal Degeneration 25*, 475-485

[22]. [22] Theotokatos, G., Escorpizo, R., Angelopoulos, T., J., Chrysagis, N., Venieri, A., Bickenbach, J., Karteroliotis, K., Grammatopoulou, E., Skordilis, E. (2024) The Sociodemographic Factors Related To Disability Of Applicants Of Welfare Benefits In Greece: A Cross-Sectional Survey Based On The World Health Organization Disability Assessment Schedule (Whodas) 2.0 *Cureus 16*

[23]. [23] Smith, A., B., Greenwood, D., C., Williams, P., Kwon, J., Petrou, S., Horton, M., Osborne, T., Milne, R., Sivan, M. (2024) Health-Related Quality Of Life In Long Covid: Mapping The Condition-Specific C19-Yrsm Measure Onto The Eq-5d-5l *Patient Related Outcome Measures 16*, 55-66

[24]. [24] Haile, L., M., Orji, A., U., Reavis, K., Briant, P., Lucas, K., M., Alahdab, F., Bärnighausen, T., Bell, A., Cao, C., Dai, X., Hay, S., I., Heidari, G., Karaye, I., Miller, T., R., Mokdad, A., Mostafavi, E., Natto, Z., Pawar, S., Rana, J., Seylani, A., Singh, J., A., Wei, J., Yang, L., F., Ong, K., Steinmetz, J., D. (2023) Hearing Loss Prevalence, Years Lived With Disability, And Hearing Aid Use In The United States From 1990 To 2019: Findings From The Global Burden Of Disease Study *Ear And Hearing 45*, 257-267

[25]. [25] Canli, S., Ozyurda, F. (2020) A Multi-Modal Exercise Intervention That Improves Cognitive Function And Physical Performance, Elderly With Mobility-Related Disability: A Randomized Controlled Trial. *The Journal Of Sports Medicine And Physical Fitness*

[26]. [26] Lin, F., Wang, Z., Zhao, H., Qiu, S., Shi, X., Wu, L., Gravina, R., Fortino, G. (2022) Adaptive Multi-Modal Fusion Framework For Activity Monitoring Of People With Mobility Disability *Ieee Journal Of Biomedical And Health Informatics 26*, 4314-4324

[27]. [27] Hassan, S., Akaila, D., Arjemandi, M., Papineni, V., Yaqub, M. (2024) Mindsets: Multi-Omics Integration With Neuroimaging For Dementia Subtyping And Effective Temporal Study *Scientific Reports 15*

[28]. [28] Mahdi, S. (2019) Tailoring And Standardizing The Assessment Of Ability And Disability In Adhd And Autism : The Development Of Who Icf Core Sets

[29]. [29] Andries, E., Lorens, A., Skarżyński, P., Skarżyński, H., Calvino, M., Gavilán, J., Lassaletta, L., Tàvora-Vieira, D., Acharya, A., Kurz, A., Hagen, R., Anderson, I., Amann, E., Heyning, P., V., D., Rompaey, V., V., Mertens, G. (2023) Implementation Of The International Classification Of Functioning, Disability And Health Model In Cochlear Implant Recipients: A Multi-Center Prospective Follow-Up Cohort Study *Frontiers In Audiology And Otology*

[30]. [30] Blyzniuk, V., Teriukhanova, I. (2024) The Role Of The Social Worker In Healthcare In The Context Of The Implementation Of The Icf In Ukraine *Ukrainian Society*

[31]. Gauthier-Beaupré, A., Battistini, B., J., Kuziemsky, C., Jutai, J. (2023) Policymaker Perspectives On Self-Management Of Disease And Disabilities Using Information And Communication Technologies *Health Research Policy And Systems 21*

[32]. Rijk, A., D., D., Carrasco-Negüe, K., Houkes, I. (2022) The Cross-Country Comparison Model For Labor Participation (Ccc Model For Lp) Of Persons With Chronic Diseases *Journal Of Occupational Rehabilitation 32*, 225-240

[33]. Selick, A., Durbin, J., Casson, I., Lee, J., S., Lunsky, Y. (2018) Promotion And Chronic Disease Prevention In Canada Research, Policy And Practice

[34]. Fragaszy, E., Quinlivan, M., Breuer, J., Craig, R., Hutchings, S., Kidd, M., Mindell, J., Hayward, A. (2015) Population-Level Susceptibility, Severity

And Spread Of Pandemic Influenza: Design Of, And Initial Results From, A Pre-Pandemic And Hibernating Pandemic Phase Study Using Cross-Sectional Data From The Health Survey For England (Hse) *Public Health Research 3*, 1-24

[35]. Brown, K., Atkin, R., Gorstein, J., Osendarp, S. (2022) Comments On Article By Pullakhandam Et Al: Reference Cut-Offs To Define Low Serum Zinc Concentrations In Healthy 1-19 Year Old Indian Children And Adolescents *European Journal Of Clinical Nutrition 76*, 1204-1205

[36]. Griffith, B., Harris, P., Grice, P., L. (2025) On The Design Of Ai-Driven Decision Support Tools In Agriculture: What Is Possible, Practical, And Useful For Land Managers And Farmers And What Is Not? *Arpha Conference Abstracts*

[37]. Mi, Q., Yang, M., Yu, X., Zhao, Z., Deng, C., An, B., Zhang, H., Chen, X., Wang, J. (2025) Mf-Llm: Simulating Collective Decision Dynamics Via A Mean-Field Large Language Model Framework *Arxiv Abs/2504.21582*

[38]. Spiller, T., R., Duek, O., Helmer, M., Murray, J., D., Fielstein, E., Pietrzak, R., H., Känel, R., V., Harpaz-Rotem, I. (2024) Unveiling The Structure In Mental Disorder Presentations. *Jama Psychiatry*

[39]. Argyris, Y., Monu, K., Tan, P., Aarts, C., Jiang, F., Wiseley, K. (2020) Developing A Vaccine Informatics To Identify Message Frames Used In Vaccine Debates On Social Media: Combining Automatic Tweet Classification And Clustering Machine-Learning Algorithms With Qualitative Content Analysis (Preprint)

[40]. Noor, N., F., M., Sipail, H., S., Ahmad, N., Annanurov, B., Noor, N., M. (2023) Covid-19: Symptoms Clustering And Severity Classification Using Machine Learning Approach *International Journal Of Integrated Engineering*

[41]. Murthy, D., Lee, J., Dashtian, H., Kong, G. (2022) Influence Of User Profile Attributes On E-Cigarette–Related Searches On Youtube: Machine Learning Clustering And Classification *Jmir Infodemiology 3*

[42]. Capasso, A., Kim, S., Ali, S., H., Jones, A., M., Diclemente, R., Tozan, Y. (2022) Socioeconomic Predictors Of Covid-19-Related Health Disparities Among United States Workers: A Structural Equation Modeling Study *Plos Global Public Health 2*

[43]. Mollalo, A., Rivera, K., M., Vahedi, B. (2020) Artificial Neural Network Modeling Of Novel Coronavirus (Covid-19) Incidence Rates Across The Continental United States *International Journal Of Environmental Research And Public Health 17*

[44]. Harville, E., Wallace, M., Theall, K. (2022) Eviction As A Social Determinant Of Pregnancy Health: County-Level Eviction Rates And Adverse Birth Outcomes In The United States. *Health & Social Care In The Community*